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A TESTBED FOR AUTONOMOUS REFLEXIVE GRASPING

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ABSTRACT

This work describes the development of a testbed which combines a subsumption architecture approach with neural network processing of tactile information in a reflexive behavior feasibility study. An overview of the tactile sensor, the neural network processor, and subsumption architecture is provided along with a plan for integrating these components into a single system. By incorporating local (reflexive) processing capabilities within a robot gripper, an additional layer of control is attained without an increased computing burden being placed on the system controller.

I. INTRODUCTION

Reflexive behavior has been demonstrated on mobile robot systems which implemented subsumption architecture [1, 2]. These behavior based control schemes were a departure from traditional control methods based on functional modules.

This work investigates the applicability of behavior based control to manipulation, specifically to a robot gripper equipped with tactile sensors. When a person touches an object that is hot or sharp his exterioceptive system triggers a reflexive reaction even before the individual becomes cognizant of the situation and initiates an intelligent response [3]. This work presents an investigation into behavior based gripper control, or autonomous reflexive grasping.

An overview of the autonomous reflexive grasping strategy and proof of concept system being developed is presented in this paper. The following section describes tactile sensors, the multi-layer perceptron neural network and backpropagation training, and the subsumption architecture. The final section of this paper discusses the details of the proof of concept system currently under development.

II. METHOD

A. TACTILE SENSORS

Tactile sensing is defined as the continuous measurement of contact pressure within an array of tactile elements or 'tactels', and is thus differentiated from touch sensing, which refers to single contact pressure measurement as with a force transducer [4]. Tactile sensors may be comprised of touch sensor arrays, however. Stansfield [5] compiled a list of 10 tactile primitives that cannot be derived but must be determined from direct measurement or computation of tactile data. These tactile primitives include object size, temperature, and mass; contact points, edges, and areas; surface texture of the object; elasticity or malleability and compliance; and the surface normal where moments about all of the Cartesian axes are zero [6]. This work focuses on tactile information describing contact points, edges, and areas that may represent an unstable grasp or potentially cause damage to the gripper.

Harmon [7] conducted a survey of industry and research personnel from which he developed the following specifications of tactile sensor requirements: spatial resolution of 1 to 2 mm, array size between 5 x 10 and 10 x 20 points per fingertip, threshold sensitivity of .5 to 10 g for one sensing element, dynamic range of 1000 to 1, stable, monotonic output, repeatable, no hysteresis, a sampling rate between 100Hz and 1kHz, rugged, inexpensive, and human skin-like. While the full set of specifications is extremely difficult to achieve, these specifications serve as guidelines for sensor development.

There are a number of different types of tactile sensors available. The brief overview which follows represents a survey of [3, 4, 6, 8, 9]. Contact switch or microswitch sensors are reliable, can withstand harsh environments, and may exhibit no hysteresis. While the greater

majority are based on metal springs, they may also be pneumatic and recent designs are being created in silicon. The major disadvantages of these switches is that they tend to provide only binary sensory information and their relatively large size limits their spatial resolution and poses mounting difficulties.

Variable capacitance sensors are constructed by placing a compliant dielectric between two conducting plates. The capacitance varies with the change in the dielectric thickness due to pressure exerted on the plates. Capacitive sensors provide good sensitivity and spatial resolution, high frequency response, and good signal to noise ratios, but they are susceptible to drift, exhibit mechanical hysteresis in the compliant dielectric element, and their signal to noise ratio is subject to degradation in the presence of electromagnetic interference (EMI) common in industrial environments. Variable capacitance sensors can also be used to sense shear because shear forces can cause the conductive plates to shift out of alignment resulting in an increase in capacitance.

Small, nigh performance optoelectronic tactile sensors, while being rugged, sensitive, resistant to EMI, and linear, pose mounting difficulties due to their fiber optics and are relatively expensive to implement. Variable inductance tactile sensors, although highly compliant, are very large and require complex transducers. Magnetic-based contact sensors exhibit design and development problems sufficient to warrant further refinement, although they appear promising. Acoustic modulation tactile sensing requires complex signal processing and planar mounting, but offers resistance to EMI and thermal effects.

Piezoelectric tactile sensors generate transient electric fields as a result of mechanical deformation or thermal absorption. They are available in very thin, highly conformable films, but due to the nature of piezoelectric material, static or steady loads cannot be measured directly. Moreover, while these sensors may be well suited to detect vibration or impact, they are highly susceptible to EMI as well as thermal noise which cannot be easily separated from a pressure response. This sensitivity to temperature allows the piezoelectric tactile sensor to also function as a temperature sensor.

Another type of tactile sensor utilizes a conductive elastomer or piezoresistive element that changes in resistance as a result of mechanical or thermal stress. Piezoresistive materials are inexpensive, highly sensitive, and tolerate wide ranges in temperature. However, many of the piezoresistive materials are noisy, nonlinear, exhibit hysteresis, drift, and fatigue at an unacceptably fast rate.

Conductive elastomer tactile sensor development has progressed to the point that commercial tactile sensors are available. These sensors have high compliance due to the relatively malleable conductive elastomer that resides between the two conductive surfaces. Though they offer high resilience, are thin and inexpensive, and are also resistant to high temperatures and corrosion, they tend to suffer from hysteresis, creep, and instability which commercial developers have attempted to reduce with specialized and proprietary conductive polymers and elastomers. The response curve of a conductive elastomer tactile sensor is also nonlinear, and cross talk reducing circuitry must be implemented in array sensor applications. Nonetheless, the good sensitivity, spatial resolution, and low cost commercial availability of conductive elastomer sensors make them an attractive choice for the proof of concept nature of this work.

The sensor chosen for initial experimentation is a conductive elastomer tactile array sensor as shown in Figure 1. This sensor utilizes a proprietary resistive ink screen printed onto two mylar sheets that are laminated together, inked sides contacting, so that the rows of ink on one mylar sheet contact the columns of ink on the opposite sheet. The actual force sensing elements are the intersections of the rows and columns. Since the ink consists of conductive particles suspended in a polymer-based binder, the resistance through the ink at any given intersection is a function of the pressure that it sees. Thus, by sequentially applying a voltage to each row and measuring the current output at each column, the array of resistance values, and thereby the array of forces, can be obtained [10,11].

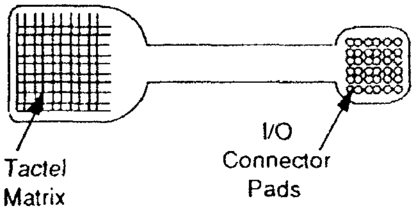

Figure 1. Tactile Sensor.

This tactile sensor contains of a 10 row X 10 column sensing matrix. Product specifications include a 5µs rise time (200kHz scanning rate), sensor thickness of .004 inches, and a spatial resolution of 0.05 inches (1.27 mm), all within Harmon's guidelines [10,11]. Actual spatial resolution, threshold sensitivity, dynamic range,

repeatability and hysteresis require further testing for quantification.

B. NEURAL NETWORKS

This project utilizes a neural network to perform tactile data processing and classification. Simply stated, a neural network is composed of many nonlinear computational elements that operate in parallel. A multi-layer feed forward architecture has been chosen for use in this project due to its success in developing pattern discriminants using continuous inputs and supervised training [12, 13]. A generalized neural network tactile information processor as compared with a logic implementation offers the advantage of large gray scale pattern recognition without requiring highly complex custom logic designs for each application.

A single layer perceptron involves a processing element that is supplied with an array of individually weighted continuous or binary inputs as shown in Figure 2. These inputs are summed with a bias and the resulting value is passed through a hard limiting nonlinear function to force it to one of two values as output. Thus, the single layer perceptron maps the input vector to an output space, with the two possible outputs being separated by a line, or hyperplane. The weights and bias for this model are calculated in a learning procedure in which inputs with known outputs are used as input patterns and the neural net converges by adjusting the weights and the bias [12].

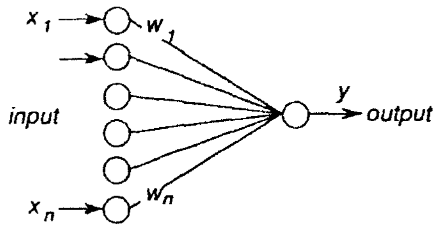

Figure 2. Single Layer Perceptron.

When the decision region is more complex than a simple two dimensional map separated by a hyperplane, two or three layers may be implemented to form a multi-layer perceptron model. Since a three layer perceptron neural network can generate arbitrarily complex decision regions, three layers are needed for non-convex decision surfaces in any multi-layer perceptron model [12].

The feed forward multi-layer perceptron is characterized by input signals being fed forward from input nodes to output nodes, and each layer feeding only the next succeeding layer. One of the primary functions that this neural network can perform is that of pattern classification. The advantage of implementing a neural net for pattern classification is that the neural net is capable of inferring a discriminant from supervised training and subsequently applying that discriminant to input patterns. The decision making capabilities of multi-layer perceptron neural networks stem from the nonlinear activation function f used within the nodes [12, 14].

For a multi-layer perceptron network as shown in Figure 3 with input layer i, hidden layer j, and output layer k, the network input to a node in layer j is

$$net_j = \sum w_{ji} o_i$$

and the output of node j is

$$o_j = f(net_j)$$

where f is the activation function, w_{ji} is the weight value for connecting link ji, and o_i is the value of the ith input layer node. While the activation function may be one of several hard limiting nonlinearities, the sigmoid activation function is generally used with backpropagation training since this algorithm requires a continuously differentiable activation function. For a sigmoidal activation function, the output of node j is

$$o_j = \frac{1}{1 + e^{-(net_j + \theta_j)}}$$

where θj is the threshold or bias parameter. Outputs for nodes in layer k are found in a similar manner [12, 14].

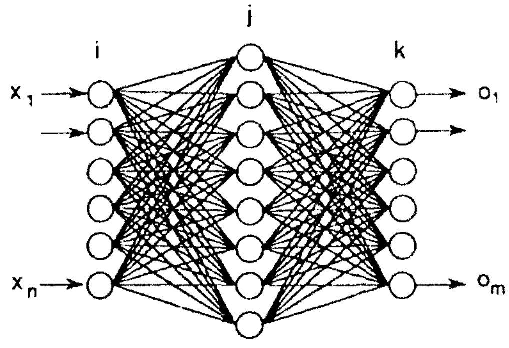

Figure 3. Multi-Layer Perceptron Neural Network.

Training for multi-layer perceptron neural networks is accomplished using back-

propagation [15]. Input patterns with desired output values are utilized by the back-propagation algorithm to determine the network weights and bias parameters. Backpropagation utilizes the generalized delta rule to minimize the average system error with respect to the adaptive weights. The average system error E is given by

$$E = \frac{1}{2P} \sum_p \sum_k (t_{pk} - o_{pk})^2$$

Convergence toward improved values for weights and thresholds is attained by taking incremental weight changes proportional to the partial of the error with respect to weight as given by

$$\Delta w_{ji} = -\eta \frac{\partial E}{\partial w_{ji}}$$

where

$$\frac{\partial E}{\partial w_{ji}} = \frac{\partial E}{\partial net_j} \frac{\partial net_j}{\partial w_{ji}}$$

Further reduction yields

$$\Delta w_{ji} = \eta \delta_j o_i$$

where η is a proportionality constant and δ_j is given by

$$\delta_{pk} = (t_{pk} - o_{pk}) o_{pk} (1 - o_{pk})$$

for output layer units or

$$\delta_{pj} = o_{pj}(1 - o_{pj}) \sum_k \delta_{pk} w_{kj}$$

for hidden layer units, with t_{pk} being the desired output value [14, 15]. A multi-layer perceptron neural network is implemented for purposes of this work.

C. SUBSUMPTION ARCHITECTURE

To initiate autonomous, reflexive gripper response from tactile stimuli, an independent layer or module that operates in parallel but independently of the main robot controller can be implemented. In human beings pure reflex control of the hand is accomplished at the spinal cord in response to sensory information. Progressively more sophisticated control is accomplished by the cerebellum, the subcortex, and the cerebral cortex [3]. While the cerebral cortex is initiating a complex movement, however, the spinal cord may still invoke a reflex movement in response to such stimuli as heat or pain, interrupting the commands from the cerebral cortex.

Brooks [1, 2] describes a layered control system that implements a hierarchical control scheme for mobile robot applications. Traditional robot control systems can be separated into functional modules that flow sequentially from sensors to actuators. The control flow from sensor to actuator might consist of perception, modeling, planning, task execution, and motor control, each interconnected and operating sequentially and dependently. Brooks implements task oriented behaviors that operate in parallel to form the robot control system. In this way, the autonomous mobile robot controller is able to contend with multiple (and possibly conflicting) goals and multiple sensory inputs in a robust and real time fashion.

This robot control system is composed of levels of competence, where each level consists of a desired class of behaviors. The lowest level is responsible for the basic reflex responses to avoid danger. The higher layers provide objectives for motion and "reasoning" with each successively higher layer describing a more specific and complex behavior. The robot control system is operational with only the lowest, or zeroth layer of the control system implemented, and the higher layers can be added at any time without compromising the existing lower layers. The higher layers inject data into the internal interfaces of the lower layers to promote their goals, and the lower layers unknowingly oblige the upper layers, provided that their goals are not compromised. This type of hierarchical control system based on parallel levels of competence is known as subsumption architecture [1, 2].

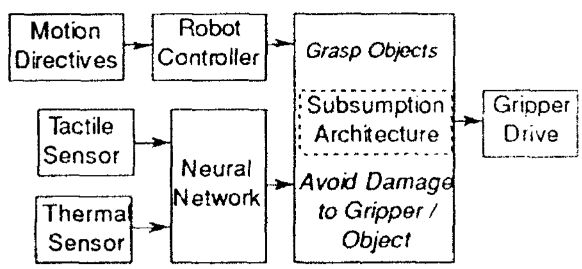

Figure 4. System Control Scheme.

This subsumption architecture can be utilized with gripper tactile sensing to provide grasping that is autonomous and reflexive. Figure 4 illustrates a possible control scheme

that may even utilize thermal sensors. The goal is to create a zeroth level of competence that operates in parallel to an existing robot gripper controller, which becomes the level 1 competence layer. In this way autonomous reflexive grasping can be implemented in existing robotic systems without modification of the existing controller.

To implement this zeroth layer responsible for reflexive response, the gripper control signals could be rerouted through the tactile sensor / neural network controller. This controller would operate in parallel to the layer 1 controller, allowing the gripper to operate in most instances as if the zeroth layer did not exist. However, in the event that the tactile sensor data was determined by the neural network to be indicative of impending danger to the gripper or to the object being grasped, the zeroth layer would subsume layer 1 and release the grip. This architecture could be extended to allow the zeroth layer or an additional layer to also detect and respond to object slippage, selective compliance requirements, and incorrect orientation, as well as providing the processed tactile data to any other level of competence for further more sophisticated actions or reasoning.

III. IMPLEMENTATION

A. DEVELOPMENTAL SYSTEM

To demonstrate the autonomous reflexive grasping proof of concept, an experimental system is being developed as shown in Figure 5. This system utilizes a tactile sensor, a personal computer based data acquisition system, and software code written in C. The tactile sensor is a 10 x 10 Tekscan sensor with an active area approximately .5 inches square, of which an 8 row x 8 column area is actually being utilized for data extraction. The sensor has silver doped electrical terminations on mylar. Interconnection of wires to the sensor has been accomplished with Ablestik Ablebond 16-1 conductive epoxy.

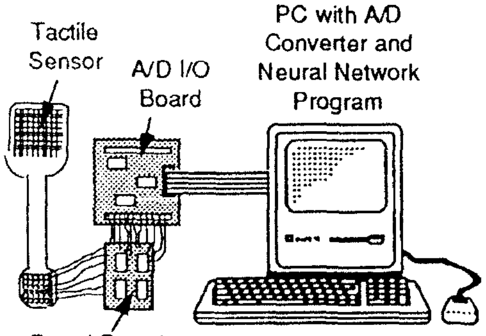

Figure 5. Experimental Tactile Sensory System.

From the tactile sensor, 8 row (input) and 8 column (output) wires are routed to a breadboard. Two multiplexers and CMOS switches allow 1 input to receive a +5 volt signal while the other 7 input wires are grounded to reduce cross talk. Op-amps provide signal amplification and current to voltage conversion for the 8 output lines. The output signals are then fed to the input channels of a DAS-8 A/D board in an IBM compatible PC, where an onboard multiplexer selects the desired channel. Digital TTL lines from the DAS-8 board are also used to time the multiplexers on the input side, coordinating the scan of the 64 tactile sensor row-column intersections. All of the functions of the DAS-8 board are selectable from C library functions, allowing integration of the tactile data extraction program, the neural network program, and the zeroth (reflex) layer of the subsumption architecture.

This system as described forms the experimental system which is currently being implemented. This system allows characterization of the tactile sensor and neural network interface, as well as training and verification of the multi-layer perceptron neural network. A parallel jaw gripper is being used for the testbed. The tactile sensor is mounted on the parallel jaw robot gripper, and the gripper controller is integrated into the subsumption architecture. The gripper is programmed to begin closing when an object enters the area between its jaws, as determined by the interruption of a light beam. The gripper closes on the object while the autonomous reflexive grasping system monitors for a dangerous grasp. If the object is sharp or pointed, the neural network causes the reflex layer of the subsumption architecture to take control of the gripper and release the object; otherwise the gripper continues to close in a normal grasping routine. In a production or commercial implementation of this system, it is assumed that the neural net could be trained and then implemented in hardware, which potentially could be located in a single chip on the gripper or in the wrist.

B. EXPERIMENTATION

The neural network program as described above is a modified generalized delta rule implementation written in C code. Operation is performed on a personal computer where the neural network program is integrated with the code to drive the sensor data acquisition, as well as the code to run the zeroth level of the subsumption architecture system. Figure 6 shows a possible behavior based control system inspired by subsumption architecture.

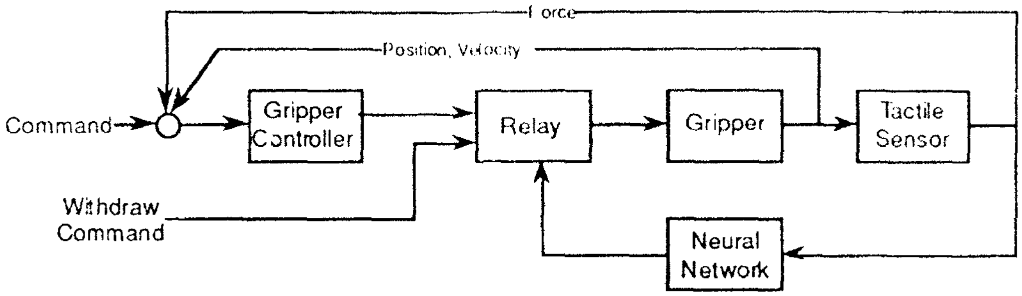

Figure 6. Implementation of behavior based control.

Initial characterization experiments of the tactile sensor have shown static resistance to peak at over 30 Mohms, with values varying from sensor intersection to intersection based on the sensor's resting position and the most recent force application. A 2lb force application to the sensor produced resistance values for a line load in the .38 to 1.5 Mohm range, depending on the orientation of the line with respect to the rows and columns of the sensor. Resistances along the line load were within a 150kohm range, with outliers of no more than 2Mohm possibly caused by inadequate fixturing. This data was extrapolated to create an ideal sample data file of horizontal line loads, point loads, and surface loads to test the capability of the neural network to differentiate these different patterns. For this experiment the line loads were located horizontally on 1 or 2 rows, while point loads could occupy only 1 or 2 intersections. Surface loads included 4 or more intersections and were square or rectangular in shape. In addition, the resistance data was subjected to an equivalent thresholding function which prevented any noise from intersections whose resistance value was greater than 2Mohms. The sensor simulated was a 4 x 4 sensor providing and input vector of 16 values.

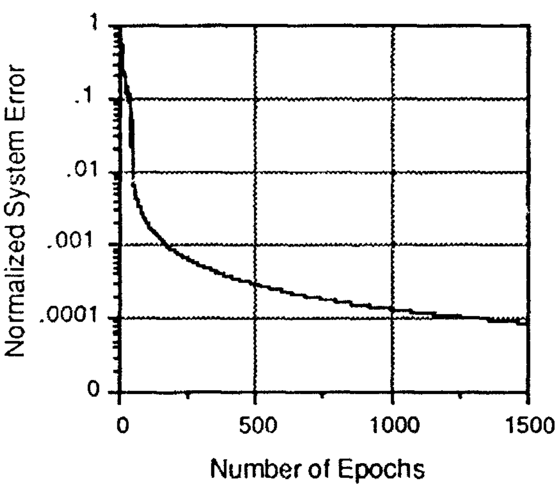

Figure 7. Typical Backpropagation Training Results.

The neural network used for this pattern classification trial had 16 input nodes, 1 hidden layer, and 3 output nodes for each of the three possible categories of point, line, or area. Convergence of the backpropagation training algorithm was achieved using 6 nodes in the hidden layer and 1500 iterations for a normalized system error of 0.000088 over 60 test patterns. The results of a typical training run are shown in Figure 7. The number of hidden nodes was determined experimentally, and it was also discovered that the network would not converge using the actual resistance values of the row-column intersection, but converged consistently when the resistance values were replaced by the difference between the noise thresholding resistance value and the resistance under load. Using the weights and bias parameters developed in this experiment, the sample data was correctly categorized by the neural network even when the resistance values supplied were 75% and 150% of the original values used for training.

Continuing experimentation will utilize the data acquisition system for faster data extraction. Experiments will focus on determining the minimum point, line, and area sizes and force values that can be detected and differentiated by the discriminant.

C. CONCLUDING REMARKS

Robots are being required to perform tasks with more dexterity and agility than previously possible. With the availability of tactile sensors and the ever present demand for safety, not just for humans but for expensive robot manipulators and target objects alike, the development of sensor driven reflexive robot control methods seems prudent. Moreover, reflexive response will probably become an even greater requirement for dexterous hands in both manipulators and prosthetic devices, both of which have delicate and expensive hardware to protect.

This work has reported on a testbed for implementation of behavior based control in a

robot gripper. Further work will address characterization of the tactile sensor and neural network, and integration of this system with a robot gripper utilizing subsumption architecture.

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